

**Original citation:**

Zubiaga, Arkaitz, Spina, Damiano, Martínez, Raquel and Fresno, Víctor. (2015) Real-time classification of Twitter trends. *Journal of the Association for Information Science and Technology*, Volume 66 (Number 3). pp. 462-473.

**Permanent WRAP url:**

<http://wrap.warwick.ac.uk/66853>

**Copyright and reuse:**

The Warwick Research Archive Portal (WRAP) makes this work of researchers of the University of Warwick available open access under the following conditions. Copyright © and all moral rights to the version of the paper presented here belong to the individual author(s) and/or other copyright owners. To the extent reasonable and practicable the material made available in WRAP has been checked for eligibility before being made available.

Copies of full items can be used for personal research or study, educational, or not-for-profit purposes without prior permission or charge. Provided that the authors, title and full bibliographic details are credited, a hyperlink and/or URL is given for the original metadata page and the content is not changed in any way.

**Publisher statement:**

'This is the peer reviewed version of the following article Zubiaga, Arkaitz, Spina, Damiano, Martínez, Raquel and Fresno, Víctor. (2015) Real-time classification of Twitter trends. *Journal of the Association for Information Science and Technology*, Volume 66 (Number 3). pp. 462-473. which has been published in final form at <http://dx.doi.org/10.1002/asi.23186> This article may be used for non-commercial purposes in accordance With Wiley Terms and Conditions for self-archiving'.

**A note on versions:**

The version presented here may differ from the published version or, version of record, if you wish to cite this item you are advised to consult the publisher's version. Please see the 'permanent WRAP url' above for details on accessing the published version and note that access may require a subscription.

For more information, please contact the WRAP Team at: [publications@warwick.ac.uk](mailto:publications@warwick.ac.uk)

The logo for Warwick Publications Wrap, featuring the text 'warwickpublicationswrap' in a white, sans-serif font on a dark background. Below the text is a yellow, stylized graphic resembling an open book or a bridge. Underneath the graphic is the text 'highlight your research' in a smaller, white, sans-serif font.

warwickpublicationswrap  
highlight your research

<http://wrap.warwick.ac.uk/>

# Real-Time Classification of Twitter Trends

Arkaitz Zubiaga<sup>1</sup>, Damiano Spina<sup>2\*</sup>, Raquel Martínez<sup>2</sup>, Víctor Fresno<sup>2</sup>

<sup>1</sup> Dublin Institute of Technology  
DIT Focas Institute, Camden Row  
Dublin 8, Ireland

<sup>2</sup> NLP & IR Group at UNED  
C/ Juan del Rosal, 16  
28040 Madrid, Spain

\* Corresponding author.

arkaitz@zubiaga.org, {damiano, raquel, vfresno}@lsi.uned.es

## Abstract

The community of users participating in social media tends to share about common interests at the same time, giving rise to what are known as social trends. A social trend reflects the voice of a large number of users which, for some reason, becomes popular in a specific moment. Through social trends, users therefore suggest that some occurrence of wide interest is taking place and subsequently triggering the trend. In this work, we explore the types of triggers that spark trends on the microblogging site Twitter, and introduce a typology that includes the following four types: *news*, *ongoing events*, *memes*, and *commemoratives*. While previous research has analyzed the characteristics of trending topics in a long term, we look instead at the earliest tweets that produce the trend, with the aim of categorizing trends early on and providing a filtered subset of trends to end users. We propose, analyze and experiment with a set of straightforward language-independent features that rely on the social spread of the trends to discriminate among those types of trending topics. Our method provides an efficient way to immediately and accurately categorize trending topics without need of external data, enabling news organizations to track and discover breaking news in real-time, or quickly identify viral memes that might enrich marketing decisions, among others. The analysis of social features as observed in social trends also reveals social patterns associated with each type of trend, such as tweets related to ongoing events being shorter as many of the tweets were likely sent from mobile devices, or memes having more retweets originating from fewer users than for other kinds of trends.

## Index Terms

twitter, microblogging, trending topics, real-time, classification



## INTRODUCTION

While social media have become mainstream, as shown by the evergrowing number of users, Twitter<sup>1</sup> stands out as the quintessential platform to openly access real-time updates on breaking news and ongoing events. With over 500 million users, Twitter sees a daily stream of more than 400 million short messages known as tweets<sup>2</sup>. These tweets include from one-to-one conversations and chatter, to updates of wider interest about current affairs, encompassing all kinds of information.

One of the appealing phenomena of the microblogging service is the fact that certain occurrences of wide interest for a community of users produce a sudden increase of mentions in real-time as they unfold. Interestingly, users live-tweet about sporting events as they watch them on TV, discuss breaking news as they learn about them, or commemorate certain events on a memorial day, among others. These result in a spiky activity associated with the occurrence in question, which produces what is known as a social trend. While these social trends can reveal what is going on at the very moment, and discover certain events and breaking news early on, a list of social trends includes just the set of terms that are being mentioned outstandingly at the very moment, but no context is provided to learn more about what triggered the social trend as well as the kind of event behind each of the trends. Little attention has been paid so far to researching social trends so as to mine additional characteristics from them and understand why they were produced. Finding out the trigger that produces a social trend can help not only inform users about social trends of their interest, but also feed third parties with different interests: for instance, news media can be interested in early discovery of social trends associated with breaking news (Zubiaga, Ji, and Knight, 2013), governments could be interested in tracking issues concerning certain events for security issues, and

1. <http://twitter.com/>

2. <http://expandedramblings.com/index.php/march-2013-by-the-numbers-a-few-amazing-twitter-stats/>

marketing professionals might be interested in quickly identifying viral memes to react accurately. In this context, previous research on the analysis of social trends has focused on long-term analysis of social conversations, but little is known about the origin of social trends with the aim of understanding and categorizing them by type to enable real-time filtering.

In this work, we set out to develop and experiment with an automatic classifier to identify the type of trigger that produces a social trend. This classifier is intended to quickly categorize trends as they emerge, allowing to inform end users about social trends in real-time in a filtered way. We introduce a typology of trends we came up with after carefully tracking and analyzing social trends for a long time, which encompasses the different kinds of triggers and enables to provide different communities with the trends of their interest. Based on our hypothesis that different types of trends will present different patterns in terms of generation and social diffusion, we define an automatic classification method that complies with the following assets to be used efficiently in real-time: (i) it requires a small and language-independent set of features that can be straightforwardly obtained, (ii) it does not make use of external data, (iii) it performs accurately outperforming a baseline approach relying on the content of tweets, and (iv) it requires low computational cost. We complement the study with an analysis of the distribution of the features we defined, bringing to light behavioral patterns for each kind of social trend, which explains how information is spread in each case.

The remainder of this paper is organized as follows. Next, we provide background on the use of Twitter, the syntax utilized by its users, and trends. Then, we introduce a typology to organize trends by type of trigger, and detail the dataset we generated to carry out the analysis and experiments. We define and analyze a set of features for characterizing trending topics and describe the trend classification experiments and results. Finally, we discuss the contributions of the study, contextualizing it with the related work and wrapping up with the conclusions.

## BACKGROUND

In this section, we provide background on Twitter relevant to this work, describing the syntax utilized by its users, and the way they interact with each other and spread information. Then, we get into detail of how Twitter presents and deals with trends (defined as *trending topics* by the microblogging system), which we utilize as the input to our trend classifier.

### Twitter

Twitter has become a huge social media service where millions of users contribute on a daily basis. Two features have been fundamental in its success: (1) the shortness of tweets, which cannot exceed 140 characters, facilitates creation and sharing of messages in a few seconds, and (2) the easiness of spreading those messages to a large number of users in very little time. Throughout the time, the community of users on Twitter has established a syntax for interaction with one another, which has become the standard syntax later officially adopted by its developers. Most major Twitter clients have implemented this standard syntax as well. The standards in the interaction syntax include:

- **User mentions:** when a user mentions another user in their tweet, an at-sign is placed before the corresponding username, e.g., You should all follow @username, she is always abreast of breaking news and interesting stuff.
- **Replies:** when a user wants to direct to another user, or reply to an earlier tweet, they place the @username mention at the beginning of the tweet, e.g., @username I agree with you.
- **Retweets:** a retweet is considered a re-share of a tweet posted by another user, i.e., a retweet means the user considers that the message in the tweet might be of interest to others. When a user retweets, the new tweet copies the original one in it. Furthermore, the retweet attaches an RT and the @username of the user who posted the original tweet at the beginning of the retweet. For instance: if the user @username posted the tweet Text of the original tweet, a retweet on that tweet would look this way: RT @username: Text of the original tweet. Moreover, retweets can further be retweeted by others, what creates a retweet of level 2, e.g., RT @username2: RT @username: Text of the original tweet. Similarly, retweets can go deeper into 3rd level, 4th, and so forth.
- **Hashtags:** similar to tags on social tagging systems or other social networking systems, hashtags included in a tweet tend to group tweets in conversations or represent the main terms of the tweet, usually referred to topics or common interests of a community. A hashtag is differentiated from the rest of the terms in the tweet in that it has a leading hash, e.g., #hashtag.

## Trending Topics

One of the main features on the homepage of Twitter shows a list of top terms so-called trending topics at all times. These terms reflect the topics that are being discussed most at the very moment on the site's fast-flowing stream of tweets. In order to avoid topics that are popular regularly (e.g., *good morning* or *good night* on certain times of the day), Twitter focuses on topics that are being discussed much more than usual, i.e., topics that recently suffered an increase of use, so that it trended for some reason. Trending topics have attracted big interest not only among the users themselves but also among other information consumers such as journalists, real-time application developers, and social media researchers. Being able to know the top conversations being discussed at a given time helps keep updated about current affairs, and discover the main concerns of the community. Twitter defines trending topics as "*topics that are immediately popular, rather than topics that have been popular for a while or on a daily basis*"<sup>3</sup>. However, no further evidence is known about the algorithm that extracts trending topics. It is assumed that the list is made up by terms that appear more frequently in the most recent stream of tweets than the usual expected (Asur, Huberman, Szabó, and Wang, 2011).

A trending topic is made up by the topic itself –i.e., the term or phrase that became a trend–, and a stream of tweets containing that topic. Table 1 shows an example of a trending topic and some underlying tweets. In this example, @u1 posted an early tweet reporting a news, which was retweeted by @u2, and by @u4 afterward; @u3 replied to @u1 by asking further information about the news, and @u5 posted a new tweet that points at a link to the news.

Trending Topic: Interpol	
User	Content of the tweet
@u1	Interpol issues arrests warrants for Gaddafi & 15 senior Libyan officials. #Libya
@u2	RT @u1: Interpol issues arrests warrants for Gaddafi & 15 senior Libyan officials. #Libya
@u3	@u1 - so Interpol cannot act until he & family leave Libya, is that right? Assuming he is top-pled?
@u4	RT @u2: RT @u1: Interpol issues arrests warrants for Gaddafi & 15 senior Libyan officials. #Libya
@u5	Interpol has issued international alert for Muammar Gaddafi & 15 other family members & close associates — Telegraph <a href="http://bit.ly/h9GwYI">http://bit.ly/h9GwYI</a>

TABLE 1  
Example of a trending topic, and some tweets associated.

In this work, we rely on trending topics as provided by Twitter through its API, therefore controlling for the detection of trends, so we can focus on the classification of social trends once they have already been detected.

## TYPOLGY OF TRENDING TOPICS

Next, we introduce the typology we use in this work to organize trending topics. After describing the typology, we detail the process of generation of a dataset, made up by trending topics and organized according to the typology.

### Definition of a Typology of Trending Topics

Not all the trending topics emerge equally. Different happenings, either in the society, on a TV show, or on the Internet, can motivate users to share and discuss on a topic, producing a sudden increase of associated sharings and subsequently the creation of a trending topic. After coming up with this hypothesis, we started tracking Twitter's trending topics while we were users of the microblogging service. This started as an informal process, where we checked the trending topics occasionally to see what was going on at the moment. When we noticed that very different kinds of events were interspersed in trending topics, we proceeded with a rather formal process of creating a list of potential categories. After discussing and defining a typology agreed by the four researchers, we continued checking trending topics for another month to make sure that the typology covered them all. This enabled us to establish the typology of trending topics that encompasses the types of conversations that arouse the interest of large communities of users in short time periods by producing trending topics. The typology we defined is composed by the following four types of triggers:

3. <http://support.twitter.com/articles/101125-about-trending-topics>

- **News:** breaking news tend to make it to Twitter early on, having even shown that on many occasions news break on Twitter before any news outlets report it (Kwak, Lee, Park, and Moon, 2010). In the course of trend monitoring, we saw that news do indeed represent a subset of trending topics in the early stage of a breaking news. We can define that a trending topic can be categorized as *news* when it is produced by a newsworthy event that major news outlets either had reported it by the time the trend popped up or will report it soon after it broke on Twitter.
- **Ongoing events:** another type of trending topic we identified was produced by a community of users tweeting about an ongoing event as it unfolds. The practice of live-tweeting an event as it is taking place has become fundamental as Twitter has gained importance as a real-time information sharing media. Here an event can be from a soccer game to a keynote presentation by Apple, a music festival, or a conference.
- **Memes:** we also identified that a portion of trending topics were triggered by viral ideas initiated by either an individual or an organization, who were usually popular enough to be able to spread something widely. We have labeled these type of trending topics as *memes*, which we can define as the event that, without being apparently newsworthy or a mainstream event that a large audience is following, makes it to a large community of users for being funny or attractive to them. It can be from a funny message by a teen heartthrob such as Justin Bieber, to a protest leader’s request to spread a message in support of a plea or complaint.
- **Commemoratives:** the last type of trending topic we identified, which was probably the least frequent, was that produced by the commemoration of certain person or event that is being remembered in a given day. We define a trending topic as triggered by a *commemorative* when users are congratulating a celebrity for their birthday, celebrate the anniversary of a certain event or person, or it is a memorial day.

Having tracked trending topics for a long period of time while we kept tweaking this typology, we believe that it can be considered as a cross-grained categorization that encompasses a vast majority of trending topics as of today on Twitter. While we believe that the presented typology includes the majority of triggers producing trends on Twitter, we did also realize that certain trends could fall into more than one of the categories described above. Even though the categorization of trends could be multi-label, assigning more than one category to each trend when applies, in this work we set out to choose the category in which a trend fits best. For instance, we consider that Liverpool supporters cheering for their soccer team as soon as they scored against Manchester United can be categorized as an *ongoing event*, and we consider as a *news* the announcement of the Defense Minister’s retreat in Germany, given that it is a newsworthy event that will be reported by news media right away.

Table 2 depicts this typology with an example of a trending topic for each of the four types.

Type	Trending topic	Description	Sample tweet
News	Islamabad	Minority Minister of Pakistan was murdered in Islamabad	RT @BreakingNews: Pakistani Minister for Minorities Shahbaz Bhatti killed in a gunattack in Islamabad - AP
Ongoing event	Anfield	A soccer game was being played at Anfield, the home stadium of Liverpool FC, an English soccer team	Liverpool vs manchester united @ Anfield :D
Meme	#5bestsoundtracks	People were tweeting their list of the 5 best soundtracks, as per request of the NME music magazine	@NMEmagazine 1. Kill Bill, 2. Trainspotting, 3. Across the Universe, 4. Juno, 5. This is England #5bestsoundtracks
Commemorative	#worldbookday	People were commemorating that it was the World Book Day	happy #worldbookday everyone! what are you reading?

TABLE 2  
Examples of trending topics for the presented typology.

Having trending topics categorized in this typology enables not only to deliver them to end users interested in specific categories, but also to feed systems that benefit from the input of trending topics with suitable categories.

## Dataset

Twitter employs an algorithm that ultimately displays the top 10 list of terms that are being discussed most at the moment. This list of top 10 terms is shown in the trending topics section on the homepage of the site, which is also available through its API. The list of trending topics obtained in real-time through the API can be complemented with another method in the API that allows to search for tweets containing a given query term, where the query term can be each of these trending topics. The search API applies to all the public tweets posted by any user on



the site, and it returns up to 1,500 of the most recent tweets. Using the top trends and search API methods, we monitored the trending topics shown on the site from March 1st to 7th, 2011. We had two processes running at the same time in order to gather both trending topics and the underlying tweets. The first process worked on the top trends API, by monitoring the trending topics appeared on the site. It requested the list of top 10 trending topics every 30 seconds. Thus, the process guarantees the detection of a trending topic almost as soon as it appears on the site, with a delay of 30 seconds in the worst case scenario. The process checked the gathered list for new trends that were not seen in previous requests. As soon as a new topic appeared in the list of trends, the second process queried the search API for the latest tweets containing the topic as a query term. It gathered thus a list of recent tweets that included the trending topic. Among the gathered information, we saved all the trending topics, and the text, timestamp, user, and language for each of the underlying tweets.

Following the above gathering process, we collected a total of 1,036 unique trending topics. These trends include a total of 567,452 tweets from 348,757 different users. Accordingly, each of the 1,036 trending topics in the dataset contains an average of about 548 associated tweets. All these tweets are written in 28 different languages, with a majority of 295,082 tweets written in English, 76,628 in Spanish, 67,673 in Portuguese, 31,685 in Dutch, and 22,863 in Indonesian. The stream of a trending topic can also include tweets written in different languages. In fact, there is not a trending topic with just one language in the dataset; 403 topics have tweets written in 28 languages, 232 have tweets in 27 languages, and 320 have tweets in 26 languages. There are just 2 trending topics with tweets in only 8 languages, and the rest include tweets in at least 12 languages. This is an evidence of the spread power of conversations on Twitter, insofar as many languages (thus assumedly many countries) contribute to share it. Taking into account the predominant language of tweets contained in each trending topic, 668 trends have a majority of tweets in English, 131 in Portuguese, 118 in Spanish, 40 in Dutch, 19 in Indonesian, 18 in German, and the remainder 42 belong to 12 different languages.

In order to perform the classification experiments, and to analyze the characteristics of the gathered trending topics, all these topics were manually annotated according to its type within the typology we defined: news, ongoing events, memes, or commemoratives. Four people, all of them being everyday Twitter users, performed the annotation process, where they had to assign each trending topic a single category from the aforementioned four types. The annotation process was divided randomly in such a way that each trending topic was annotated by three of the annotators. The annotators carefully read through the tweets in a trending topic, so they could understand what was going on, assigning the category that better suited. When tweets were written in a language that the annotator in question could not understand, Google's translation system<sup>4</sup> was used to facilitate the task. The annotation process produced the following distribution of categories: 616 ongoing events (59.5%), 251 memes (24.2%), 142 news (13.7%), and 27 commemoratives (2.6%). In order to measure the inter-annotator agreement we computed the Fleiss' Kappa coefficient (Fleiss, 1971), obtaining a value of 0.597. According to Landis and Koch (1977), kappa values between 0.4 and 0.6 may be taken to represent 'moderate' agreement beyond chance<sup>5</sup>.

The trending topics and its annotations used in this work are publicly available for further research<sup>6</sup>.

## CHARACTERIZATION OF TRENDING TOPICS

Next, we present the classification experiments as well as the feature analysis, with which we evaluate and quantify the validity of the introduced typology. We first analyze and discuss the features, and then present classification experiments based on those features.

### Features of Trending Topics

The main motivation of this work is our hypothesis that depending on the type of trigger that produces a trend, the social patterns observed on users' behavior in terms of information diffusion will vary. Having this hypothesis as a motivation and starting point, we define a set of 15 social features to help capture this social behavior. We analyze the extent to which these features identify behavioral patterns so as to accurately categorize trends in real-time. Later, we dig into these social features to extract insight about what they mean in each type of trend.

As an approach to discovering the type of trigger behind a trending topic, we propose 15 social features that consider the way it spreads. Furthermore, since we want to categorize a trending topic as soon as it appears trending on the site, the features must be straightforward, easy to get, and cheap to compute while the system performs accurately. Note that the number of tweets in a topic that just trended is relatively small (average of 548 tweets), thus computing the features is fast and computationally cheap. This would ensure the immediacy of the computation, and the ability to predict the type of a trending topic on the fly, as soon as it appears on the Twitter's

4. <http://translate.google.com/>

5. Note that the range of possible values for Fleiss' Kappa coefficient includes values below zero. In this case, a 0.597 Kappa is the equivalent to 90.5% agreement rate among annotators.

6. <http://nlp.uned.es/~damiano/datasets/TT-classification.html>

list. Moreover, these features are independent of the language used in tweets, and do not depend on the vocabulary utilized by users.

We believe that each type of trending topic spreads in a different way, and that social features have much to do with the type. Our conjecture is that trending topics brought about by different types of trigger will be socially shared in a different way. For instance, one could expect that tweets about news tend to be accompanied by links more than ongoing events, or that memes could be shared and spread in a different way as compared to other types.

The 15 social features we propose for characterizing trending topics are shown in Table 3. The table shows both the name and an explanatory definition for each feature. The features are organized in two groups, according to the type of calculation used.

On one hand, we use average number of occurrences of features in the tweets corresponding to a trend. Each average computed as the arithmetic mean is the result of dividing the number of occurrences of the corresponding feature in the whole trend by the total number of tweets gathered for the trending topic (see Equation 1).

$$AM(f)_t = \frac{1}{|T|} \sum_{i=1}^{|T|} f_i \quad (1)$$

where  $AM(f)_t$  is the arithmetic mean of feature  $f$  for the trending topic  $t$ ,  $|T|$  is the number of tweets in the trending topic, and  $f_i$  is the value of feature  $f$  for the tweet  $i$ .

We propose 10 different features that rely on average values: *Retweets (depth)*, *Retweets (ratio)*, *Hashtags*, *Length*, *Exclamations*, *Questions*, *Links*, *Topic repetition*, *Replies*, and *Spread velocity*. All these features can be computed by following Equation 1, except the *Spread velocity*, which follows a slightly different equation to compute the average number of tweets posted per second (see Equation 2).

$$AM(sv)_t = \frac{|T|}{\Delta t} \quad (2)$$

where  $\Delta t$  = is total number of seconds from the first to the last tweet in the trending topic.

On the other hand, we compute the diversity of feature values all across the tweets that belong to a trending topic. The diversity calculates the variation of the feature throughout the trending topic. The higher is the diversity value, the more different is the feature from tweet to tweet within a trending topic. To compute the diversity, we use Shannon's diversity index (see Equation 3). In other words, Shannon's index is the information entropy of the distribution of values for a feature, i.e., each different value is considered a symbol, and the population of each value is used as the probability.

$$H'(f)_t = - \sum_{j=1}^S (p_{jt} \ln p_{jt}); \quad p_{jt} = \frac{n_{jt}}{N} \quad (3)$$

where  $H'(f)_t$  is the Shannon's index of feature  $f$  for the trending topic  $t$ ,  $n_{jt}$  is the population of the value  $j$ ,  $S$  is the number of different values,  $N$  is the total population, and  $p_{jt}$  is the observed probability of the value  $j$ .

We propose 5 features that rely on diversity: *User diversity*, *Retweeted user diversity*, *Hashtag diversity*, *Language diversity*, and *Vocabulary diversity*.

## Understanding the Features

Next, we analyze and discuss the studied features, not only for the Twitter features, but also for the textual content of tweets. To do so, we explore the distributions of the Twitter features for each type of trending topic, and dig into the main terms that characterize each of the types. This helps understand whether and why the features we used discriminate among types of trending topics.

### Analysis of Twitter Features

The use of Twitter features produced an accurate performance for classifying trending topics according to the proposed typology. Going further, it is of utmost importance to analyze how the values of these features distribute for each type of trending topic, and the extent to which they can help discriminate types. We rely on box/whisker plots to show these distributions of values, and differences or similarities between types. Each box/whisker plot shows the distribution of values of a feature for the 4 types of trending topics. The line in the middle of the box is the median (second quartile), the bottom of the box is the first quartile, the top of the box is the third quartile, and the top bar is the maximum value observed where the bottom bar is the lowest. This kind of plot helps visualize the range of values for each feature, as well as see where most of the values congregate. It enables to perform a qualitative analysis of the features.

Averages / Arithmetic Means	
Feature	Definition
<b>Retweets (depth)</b>	Average number of retweet levels in tweets. The retweet level of a tweet is the number of retweeting users before it reached the current state. For instance, the retweet of an original tweet corresponds to level 1, the retweet of a retweet to level 2, and so on. This feature adds up all these levels, and divides it by the total number of tweets.
<b>Retweets (ratio)</b>	Ratio of tweets that contain a retweet. It is the result of dividing the number of tweets that are retweets (regardless of the level) by the total number of tweets.
<b>Hashtags</b>	Average number of hashtags in tweets.
<b>Length</b>	Average length of tweets, i.e., the average number of characters used.
<b>Exclamations</b>	Number of tweets with exclamation signs. Tweets with at least an exclamation are given a value of 1, whereas tweets without exclamations are given a value of 0. This feature computes the average of those values.
<b>Questions</b>	Number of question signs in tweets. It is the same as with exclamations, but with question signs.
<b>Links</b>	Average number of links in tweets
<b>Topic repetition</b>	Average number of uses of the trending topic in tweets. The term corresponding to the trending topic may appear more than once in a tweet, especially when users repeat it to make it stronger and trend.
<b>Replies</b>	Average number of tweets that are replies to others. A tweet is given a value of 1 when it is a reply to another user, or a value of 0 otherwise.
<b>Spread velocity</b>	Average number of tweets per second in the trend. It is the result of dividing the total number of tweets by the period of time between the last and first tweets in the trend.
Diversity values	
Feature	Definition
<b>User diversity</b>	Shannon's diversity index of users who posted tweets. When a few users are repeatedly tweeting on the topic, the diversity decreases.
<b>Retweeted user diversity</b>	Shannon's diversity index of users who were retweeted in the trend (not the user who retweets). The diversity value is higher when different users get retweeted, and lower when retweets come from a few users.
<b>Hashtag diversity</b>	Shannon's diversity index of hashtags included in the trend. When the same hashtag is used throughout a trend, the diversity decreases.
<b>Language diversity</b>	Shannon's diversity index of languages used in the trend. The diversity is lower when most of the tweets are written in the same language, and higher when several languages have some tweets.
<b>Vocabulary diversity</b>	Shannon's diversity index of terms contained in the trend. The diversity decreases when tweets share a similar vocabulary, whereas it increases the vocabulary varies among tweets.

TABLE 3  
List of Twitter features and definitions.

Figures 1 and 2 show sets of box/whisker plots for average and diversity features, respectively. At a first glance, it can be seen that none of the features provide the same range of values for all the types of trending topics, so that all of them seem to be useful to some extent as to discriminating types. Analyzing them in more detail, some interesting thoughts can be inferred:

- Figure 1(b) and 1(a) show that the use of retweets is more frequent for memes, and to a lesser extent for news. The use of retweets in memes seems to be due to the virality of this kind of trending topics.
- Figure 1(b) showing the ratio of retweets contained in the trend shows that news and memes are retweeted most. Figure 1(a), which is very similar, shows that the retweeting depth of news and memes is very similar to the other, due to its high resemblance to the figure showing retweet ratios.
- Figure 1(c) shows that, while the ratio of hashtags is very similar for breaking news and ongoing events, some of the memes and commemoratives have a higher ratio of hashtags. Interestingly, few commemoratives have tweets with more than one hashtag.
- Figure 1(d) shows that tweets posted during ongoing events are significantly shorter than those in the other classes. Intuitively, users who are tweeting about an ongoing event are likely to either be attending (e.g., a conference) or watching (e.g., a TV show) an event. This suggests that while users are following another event,



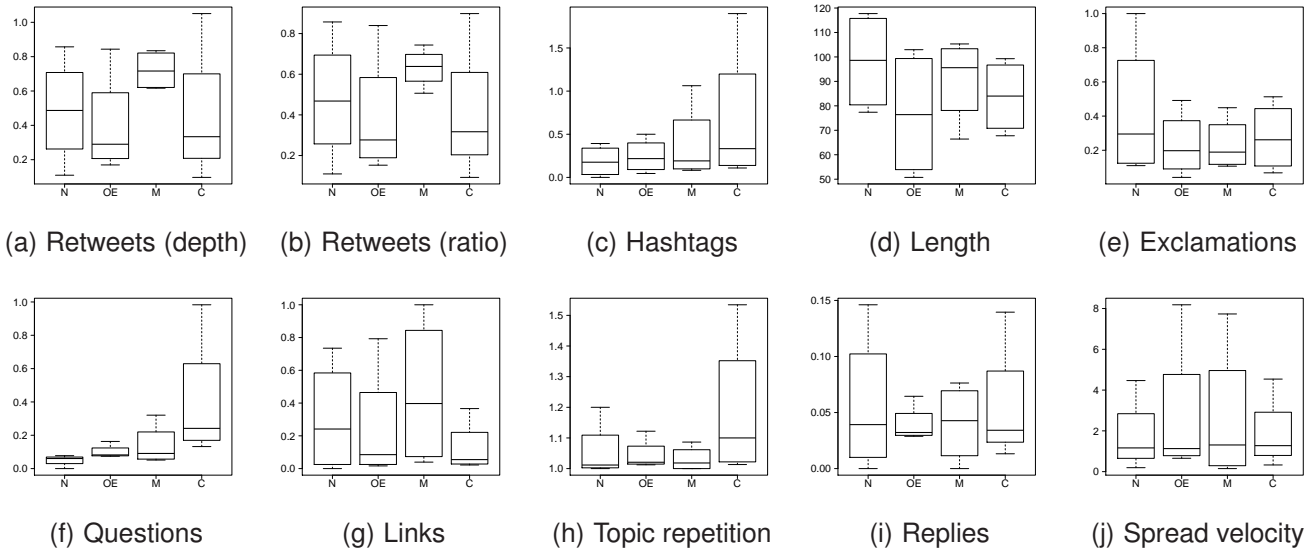


Fig. 1. Box/whisker plots for features relying on average values (N: News; OE: Ongoing Events; M: Memes; C: Commemoratives).

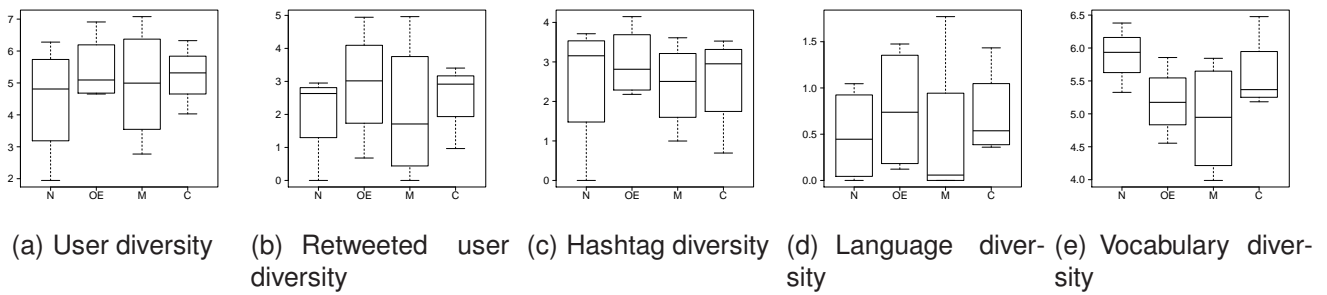


Fig. 2. Box/whisker plots for features relying on diversity values (N: News; OE: Ongoing Events; M: Memes; C: Commemoratives).

they devote less time to sending the tweet, either because of the lack of attention or time, or because they are using a hand-held device where writing requires more effort.

- Figure 1(f) shows that questions marks are used more frequently in commemorative trending topics. This suggests that users tweeting about commemorative issues are rather prone to asking about it. The use of questions marks is the lowest for news, where users are not so likely to ask, but rather get surprised because of the news (see the high use of exclamations in news in Figure 1(e)).
- Regarding the use of links in tweets, one could expect that news clearly had the highest density of links. However, Figure 1(g) shows that memes have more links. This is due to the fact that several memes emerge from sharing links to funny content on the Web. On the other hand, the number of links in news is not that high. This corroborates the observation by Kwak et al. (2010) that sometimes news break earlier on Twitter than on the Web, thus not always there are links available as soon as the topic trends on Twitter. This strengthens the motivation to discover breaking news that trend on Twitter.
- Figure 1(h) shows that the feature considering the repetition of the trending topic is not discriminative for news, ongoing events, and memes, but it presents a higher rate of repetition for commemorative trends.
- As regards to the spread velocity of the trends, Figure 1(j) shows that there is some similarity among types, but some memes and ongoing events spread faster and have higher frequencies of tweets per second.
- Figure 2(a) shows that the diversity of users contributing to the trending topic is uniformly distributed over the four classes. Nonetheless, it is worthwhile noting that the values are very low. This suggests that trending topics are usually generated by a small number of users. This corroborates the conclusion by Asur et al. (2011) that a few users can be considered *trend-setters*, who provide the seed that starts the trend, and loads of *propagators* help spread it.
- Figure 2(b) shows the diversity of users who got retweeted in a trend. It can be seen that memes present

the lowest diversity, followed by news, whereas the highest diversities occur in ongoing events and commemoratives. This means that the contribution of influential users is clearer for memes. Thus, there are fewer *trend-setters* that spark the emergence of memes.

- Figure 2(d) shows the diversity of languages of the tweets contained in trends. It shows that there are lots of memes with a low diversity of languages, where there is a predominant language in which most tweets were written. It seems that most tweets in memes are spread in the same language that it was started. The fact that memes are the most retweeted type of trend is relevant for this, since retweets retain the language of the original tweet. Ongoing events are the trends that show the highest diversity of languages, suggesting that many of the events are followed internationally –e.g., soccer games.
- Figure 2(e) shows higher vocabulary diversity for news and commemoratives. However, this higher diversity for news and commemoratives does not affect hashtags significantly, where diversity is comparable to the other types of trends (see Figure 2(c)). This suggests that the increase of diversity is produced by content other than hashtags, which could be explained with other factors such as longer, wordier tweets for news.

### Analysis of Text in Tweets

In order to analyze the textual content of the tweets, we give an overview of the top terms occurring in each type of trending topic, i.e., the most frequent vocabulary used in each type of trending topic. To do so, we first performed a filtering process to remove irrelevant words. The filtering process removed all the stopwords contained in the tweets. The stopword removal process includes Twitter-specific words like *RT*, and words in stopword lists for the main languages in the dataset. After that, we computed the TF (term frequency) of each word for each type of trending topic. This process produced a list of words for each type of trending topic, ranked in a descending order by TF value. Table 4 shows a list of top 15 terms for each type of trending topic. It can be seen that several words in these lists have strong relation with the definitions of the types of trending topics:

- For the commemorative trending topics, congratulating words stand out –e.g., *happy* and *birthday*–, as well as time-related words –e.g., *day* and *anos* (years in Portuguese)–, showing that most tweets have to do with celebrations and congratulations.
- For the trending topics related to ongoing events, several words refer to the present –e.g., *tonight* and *live*–, the action they are doing –e.g., *watching* and *watch*–, or the media they follow –e.g., *tv*–. This shows that this kind of trending topic has some specific terminology associated, which is strongly related to happenings that are being live-tweeted.
- For the news-related trending topics, the terminology is not that specific. It seems that most of the top terms are named entities that appear frequently in the news. However, including the word *news* itself seems frequent for this kind of trend, as it is the top term in this class.
- The terminology associated to memes seems to be the least specific. This makes sense because the range of topics covered by memes can be very wide, and it seems that the vocabulary of a meme can vary substantially. Note that a meme can be any of a funny thing, something that users are keen to happen or see, or an idea that unintentionally went viral.

Further, it seems that some terms tend to overlap across different classes. For instance, terms related to the actor Charlie Sheen appear as top terms for news, ongoing events, and memes. He had different trending topics in the time frame of our dataset: (1) users retweeted actor’s message thanking the Twitter community for following him –meme–, (2) he broadcasted a live show on the Internet –current-event–, and (3) he was fired from the TV series *Two & a Half Men*.

## AUTOMATIC CLASSIFICATION OF TRENDING TOPICS

Next, we describe the technical details of the classifier used in our experiments to classify trending topics. Afterward, we present the results of assessing the accuracy of the classifier, as well as the appropriateness of the typology introduced in this work.

### Experimental Setup

In order to evaluate the suitability of classifying trending topics according to the established typology, we perform classification experiments using Support Vector Machines (SVM) (Joachims, 1998). Being a multiclass task, we specifically rely on a *one-against-all* binary combination method (Rifkin and Klautau, 2004), implemented with *svmlight*<sup>78</sup>. Instead of considering the multiclass problem as a single task, *one-against-all* splits it into smaller binary

7. <http://svmlight.joachims.org>

8. We use the linear kernel and set the penalty parameter  $C$  –which controls the trade off between allowing training errors and forcing rigid margins– to 5, allowing a certain degree of misclassification. Those parameters were found suitable for another text classification task (Zubiaga, Martínez, and Fresno, 2009), i.e., classification of web pages using metadata from social media.

N	OE	M	C
news	love	charliesheen	happy
sheen	watching	winning	birthday
charlie	lol	love	mamonas
guttenberg	tonight	twitter	gainsbourg
half	live	lol	assassinat
men	good	day	bon
twitter	video	lmaotwitpics	jon
john	watch	justinbieber	jovi
jane	david	video	day
fired	game	devassa	anos
russell	time	great	serge
sky	tv	stone	bieber
lina	idol	adriesubono	justin
game	sheen	boy	jensen
warner	jones	movie	ackles

TABLE 4

List of top terms in tweets grouped by type of trending topic (N: News; OE: Ongoing Events; M: Memes; C: Commemoratives).

ones. For a problem with  $k$  classes, *one-against-all* defines  $k$  different classifiers. In the training phase, each of the  $k$  classifiers learns a model to separate a class from the rest  $k-1$ . This model creates a hyperplane to separate the class from the rest. In our task, where 4 classes are defined, the following classifiers are created: 1 vs 2-3-4, 2 vs 1-3-4, 3 vs 1-2-4 and 4 vs 1-2-3. In the process of categorizing, each classifier provides an output for each trending topic, which refers to the margin –i.e., distance to the hyperplane– as a reliability value. The classifier maximizing the output defines the final class predicted by the system (see Equation 4).

$$\hat{C}_i = \arg \max_{i=1,\dots,k} m_i \quad (4)$$

where  $m_i$  is the margin outputted by the classifier  $i$ .

We use two different representations in the classification process: the Twitter features analyzed above, and a bag-of-words approach of the textual content of tweets as a baseline. With both representations, we rely on the Vector Space Model (VSM), thus we define a vector for each trending topic. We create one vector per trending topic for each of the representations. We use a training set with 600 trending topics, with 436 in the test set. We perform 10 random selections from the dataset to form 10 training datasets so we show the average results in the tables. The two representations we use are the following:

- For the Twitter features, we use vectors with 15 dimensions. The dimensions correspond to the social features introduced above. All the trends have a value for each of this dimensions, so that there are no features that remain without a value. The main advantages of this representation approach are the straightforwardness of the features, and that the number of features does not depend on the number of trends we have to represent, but it remains unchanged.
- For the textual content of tweets, we rely on the bag-of-words approach. We tokenize tweets and compute the number of occurrences of each term in a trend. Prior to that, we remove stopwords for the main languages in the dataset. Note that tweets have not been translated. Hence, the vocabulary used to represent the tweets includes the terms from all the languages in the collection. We represent each trend with the TF values of each term. This approach is computationally much more expensive than the approach based on Twitter features, and presents the problem that the number of dimensions utilized to represent the trends increases as the collection grows. In this case, representing the 1,036 trending topics generated vectors with 512,943 dimensions.

Finally, we rely on the fact that the larger is the margin outputted by a classifier for a class, the more reliable can be considered the classifier’s prediction on that class. Based on this idea, we use classifier committees (Sun, Huang, Guo, and Zhao, 2004) to combine the outputs of classifiers based on Twitter features and the bag-of-words. Classifier committees add up the outputs of both classifiers. Note that, in this case, there are two classifiers (one based on Twitter features, and the other based on the textual content of tweets), and four classes as defined in the typology. Thus we can get the sum of the outputs from both classifiers for each class. Afterward, the class with the highest sum value is selected as the prediction of the committees (see Equation 5).

$$C_t^* = \arg \max_{i=1..k} \{S_{ti}\} \quad (5)$$

where  $k$  is the number of classes,  $t$  is the trending topic, and  $S_{ti}$  is the sum given by Equation 6.

As an example of the possible advantage of using classifier committees, Table 5 shows the outputs from the two classifiers for a trending topic. Even though one of the classifier labels the trending topic as news, and the other labels it as meme, adding up outputs using classifier committees changes the label to ongoing event. Classifier committees can be suitable in some cases to get the most from both classifiers.

	N	OE	M	C
Classifier A	1.2	1.1	0.6	0.3
Classifier B	0.5	1.0	1.2	0.3
Classifier committees	1.7	2.1	1.8	0.6

TABLE 5

Example of classifier committees on a trending topic. Classifier A labels it as news, and classifier B labels it as meme, while adding both up using classifier committees would label it as an ongoing event.

$$S_{ti} = \sum_{v=1}^{|V|} m_{v ti} \quad (6)$$

where  $|V|$  is the number of classifiers, and  $m_{v ti}$  is the margin outputted by the classifier  $v$  for the trending topic  $t$  in the class  $i$ .

## Evaluation

	Accuracy	Kappa
Bag-of-words	.752	.530
Twitter features	.784	.604
Committees	.812	.649

TABLE 6

Accuracy and Cohen’s Kappa statistic of the trend classification by type of representation.

	Class Precision			
	N	OE	M	C
Bag-of-words	.673	.783	.636	.548
Twitter features	.634	.829	.731	.132
Committees	.598	.941	.687	.200

TABLE 7

Precision by class (N: News; OE: Ongoing Events; M: Memes; C: Commemoratives) of the trend classification by type of representation.

Table 6 shows the accuracy values of the classification of trending topics. The accuracy measures the percent of correct guesses among all the predictions. The representation based on the proposed Twitter features achieves a superior accuracy than the bag-of-words baseline. This superiority gap is of 3.2% in favor of the representation based on Twitter features. Furthermore, the winning approach presents the advantages that it only requires 15 features instead of the thousands required by the content-based representation and, the features are straightforward and easy to compute. When analyzing in more depth the precision by class (see Table 7), it can be seen that Twitter features perform better in the detection of ongoing events, and especially memes, where the gap is bigger than 9%. Using the bag-of-words improves for news, and especially for commemoratives, where Twitter features get low precision. However, this could be due to the small number of commemoratives in the collection<sup>9</sup>, and it may perform better with more trends of this type, probably providing a better representation of the class in the training stage.

9. Note that there are only 27 commemorative trends in the collection.

The use of classifier committees combining the outputs of both classifiers yield even superior results. It improves the performance of the use of Twitter features by 2.8%. As [Sriram, Fuhry, Demir, Ferhatosmanoglu, and Demirbas \(2010\)](#) report for the classification of single tweets, our work also shows that the combination of bag-of-words with Twitter features yields better results in the classification of trending topics. However, this outperformance comes especially because of the high performance of the committees on ongoing events. Single classifiers perform better than the committees for the rest of the classes. Moreover, it requires both classifiers –Twitter features and bag-of-words– to be run first, in order to perform the combination afterward. The use of committees can be a good option to detect ongoing events when immediacy is not a key requirement.

Due to the fact that classes are unbalanced, accuracy values may be subject to guesses given by randomness. Thus, the accuracy does not always compensate for hits that can be attributed to randomness ([Ben-David, 2007](#)). Because of this, we also show the Cohen’s Kappa statistics ([Cohen, 1960](#)) to measure the extent to which accuracy values are independent of randomness (see Equation 7).

$$\kappa = \frac{P_0 - P_c}{1 - P_c} \quad (7)$$

where  $P_0$  is the relative observed agreement between the predictions of a classifier and the observed categorization (accuracy), and  $P_c$  is the hypothetical probability of chance agreement, using the observed data to calculate the probabilities of each observer randomly saying each category. If the categorizations are in complete agreement then  $\kappa = 1$ . If there is no agreement between the categorizations, then  $\kappa = 0$ .

The kappa values in Table 6 show the impact of randomness on the agreement between predicted and observed categorizations for the 3 classifiers. Note that the higher is the value, the lower is the effect of randomness on the accuracy improvement. It can be observed that the kappa values follow the same rank as the accuracy values, so that it indicates that the accuracy improvement is not a consequence of random guesses.

## DISCUSSION

This study attempts to satisfy the dearth of research analyzing, characterizing, and classifying social trends in their early stage, with the aim of feeding systems that can benefit from real-time knowledge. As such, it is not only relevant for researchers studying trends in social media, but also for developers who are eager to enhance their systems with real-time data from social networks. The typology of trends and methodology introduced in this paper enable us to serve the social trends of interest to different audiences: (i) the identification of trends categorized as *news* can help discover breaking news early on, which would considerably facilitate the task of tracking social media for journalism practitioners, which has become paramount in their daily newsgathering process ([Zubiaga et al., 2013](#)), (ii) the identification of *ongoing events* can feed an event summarization system (e.g., [Zubiaga, Spina, Amigó, and Gonzalo \(2012\)](#)), which would quickly be informed that a new event of wide interest is going on and is potentially worth being summarized, (iii) the identification of *memes* can be a powerful input to marketing decisions ([Williams, 2000](#)), to find out the topics of interest and viral concepts that succeed at the very moment, as well as for researchers in the social sciences, to study the virality of ideas online, and (iv) the identification of *commemorative* trends, which might often be known beforehand, might be interesting to mine and analyze the way they emerge, how they are spread, and what opinions or comments users associate with them ([Pak and Paroubek, 2010](#)). Here we have listed a set of systems that can benefit from the output of a set of categorized social trends, which is not intended to be comprehensive, and we believe that it can be extended to numerous systems that can benefit from knowledge about the current status of the society.

While the typology of trends introduced in this work can be too cross-grained for certain applications, it can be easily extended by breaking down the categories into smaller subcategories. As an example from existing research, [Recuero, Amaral, and Monteiro \(2012\)](#) study a specific type of memes, which they call fandom memes. Fandom memes can be defined as the memes that are introduced by a large community of a celebrity’s or groups fans. These specific memes can be categorized as a subcategory of memes in our typology, which could in turn be classified into more specific fandom memes depending on the type of fan, i.e., supporters of a political party, a soccer team, or a music band. Likewise, breaking news can be classified in terms of the type of diffusion, e.g., multiple contributors –as in the Arab spring– or few authoritative sources –CNN–. Rather than presenting an exhaustive low-level categorization of trending topics, this study pretends to be comprehensive in the analysis of features that characterize trends, to understand and be able to categorize them.

In this work, we relied on trending topics as provided by Twitter itself, controlling for the identification of trends on our end. Given that Twitter’s algorithm for trend detection is not public, we cannot certify that this is the optimal solution. The use of alternative algorithms for trend detection would help quantify the effect of such step, which is not within the scope of this work. Besides that, as a future work we are planning to study how each type of trending topic evolves in the subsequent minutes/hours, especially to explore whether some trends evolve into a



different kind of trend, e.g., how a widely known phenomenon such as the *Harlem Shake*, which began as a meme, made it later to most news outlets in the form of a news story.

## RELATED WORK

Twitter has become an essential platform for researchers studying social information sharing. Researchers have studied the microblogging phenomenon itself (Java, Song, Finin, and Tseng, 2007; Kwak et al., 2010; Boyd, Golder, and Lotan, 2010), the information diffusion on the social network (Wu, Hofman, Mason, and Watts, 2011; Krishnamurthy, Gill, and Arlitt, 2008; Yang and Leskovec, 2010) as well as the content of tweets (Jansen, Zhang, Sobel, and Chowdury, 2009; Sriram et al., 2010; Sakaki, Okazaki, and Matsuo, 2010; Hurlock and Wilson, 2011; Cheng, Caverlee, and Lee, 2010).

Regarding classification of single tweets, Sriram et al. (2010) define a typology of five generic classes of tweets (news, events, opinions, deals, and private messages) in order to improve information filtering. The authors represent tweets using a small set of language-dependent features to classify tweets written in English. The use of these features outperforms the bag-of-words approach in the classification of tweets according to the typology.

Castillo, Mendoza, and Poblete (2011) define a set of features associated to tweets, users, topics and the propagation of retweets in order to automatically classify news events on Twitter as credible or not credible, so as to detect misinformation or false rumors. They show the effectiveness of user and sentiment-based features to this end.

Little work has been done analyzing the properties of trending topics on Twitter. Most of them focus on event and topic detection (Asur et al., 2011; Cataldi, Di Caro, and Schifanella, 2010; Sakaki et al., 2010; Albakour, Macdonald, and Ounis, 2013; Zhao, Shu, Jiang, Song, Yan, and Li, 2012) or summarization of scheduled events in real-time as the events unfold (Zubiaga et al., 2012). Asur et al. (2011) explore the longevity of trending topics on Twitter, and analyze the role of users in the emergence of trends. They found that (i) a few users are *trend-setters*, i.e. early contributors in the emergence of a trend, and (ii) a larger group of users are *propagators*, who help spread the topic. Cheong and Lee (2009) and (Kwak et al., 2010) analyze the evolution of trending topics over the time, and perform a qualitative study of social features that characterize trending topics.

Cui, Zhang, Liu, Ma, and Zhang (2012) categorize hashtags to discover vocabulary associated with news, filtering out memes, idioms and advertisements. They make use of features of hashtags based on temporal behavior, authors' distribution and word splitting to capture meme probability over popular hashtags in a six-month Twitter dataset.

Recuero et al. (2012) study the strategies used by fans and anti-fans of music bands to generate trending topics. This type of trending topics can be considered a particular type of memes. They define five types of fan-based trending topics: Tribute, Promotion, Response, Request and War.

Kairam, Morris, Teevan, Liebling, and Dumais (2013) study how to engage users of a search engine with social media when querying about trending events. They achieve a substantial agreement categorizing a sample of 99 trending events –from Twitter's trending topics and Bing's Popular Now search queries– and considering the categories Breaking, Ongoing, Meme, Commemorative and Unknown.

Complementary to our trending topics' taxonomy, Naaman, Becker, and Gravano (2011) define a taxonomy of trending topics, focusing on characterizing local events (e.g., in a city) as endogenous trending topics – those that emerge within Twitter and do not correspond to external events – from exogenous trending topics – that is, trends caused by real events that propagate through social media. As the authors explain, a trend is represented with a long time window (tweets sharing the trending topic terms 72 hours before and after the trend's peak, 1k tweets in average).

Different from the above, our work considers the following novel aspects that, as far as we know, had not been addressed before: (i) we define a high level typology that encompasses Twitter's worldwide trending topics, and (ii) we describe a system and features that accurately identify, in real-time, the type of trigger that sparks a trending topic, instead of considering the whole lifetime of a trend.

## CONCLUSIONS

In this work, we have explored the types of triggers that spark conversations on Twitter. Specifically, we have explored the top conversations shown as trending topics on the site. We have introduced a typology to organize Twitter's trending topics by the type of happening that caused them. This typology includes the following 4 types of trending topics: *news*, *ongoing events*, *memes*, and *commemoratives*. We aimed at characterizing trending topics so that we were able to organize them by type. To this end, we have set out 15 straightforward features to represent trending topics. These features are independent of the language used in the tweets, and rely on the social diffusion of the trending topic. The features are of two different types: averages, and diversity values.

We have performed classification experiments using SVM classifiers to study the usefulness of these features to discriminate types of trending topics. We have shown that the proposed features provide more accurate classification results than the use of textual content of tweets. Furthermore, these features can straightforwardly be computed, and

only require tweets sent before the topic trended, without need of external data. The proposed method provides an immediate way to accurately organize trending topics using a small amount of features. Unlike for the content-based representation, the number of features remains unchanged, and does not increase as the collection grows.

We have also analyzed and studied the nature and characteristics of the proposed features. The qualitative analysis of features provides deeper insight to understand how different happenings spread on social media. We have proven that the proposed features can help discriminate the type of trigger that caused the trending topic.

## ACKNOWLEDGMENTS

This work has been part-funded by the Spanish Ministry of Education (FPU grant nr AP2009-0507), the Spanish Ministry of Science and Innovation (Holopedia Project, TIN2010-21128-C02), the Regional Government of Madrid and the ESF under MA2VICMR (S2009/TIC-1542) and the European Community's FP7 Programme under grant agreement nr 288024 (LiMoSiNe).

## REFERENCES

- Albakour, D. ; Macdonald, C. , and Ounis, I. . Identifying local events by using microblogs as social sensors. In *Proceedings of OAIR 2013, the 10th Conference on Open Research Areas in Information Retrieval*, Lisbon, Portugal, 2013. Springer.
- Asur, S. ; Huberman, B. A. ; Szabó, G. , and Wang, C. . Trends in social media : Persistence and decay. *CoRR*, abs/1102.1402, 2011.
- Ben-David, A. . A lot of randomness is hiding in accuracy. *Engineering Applications of Artificial Intelligence*, 20(7): 875 – 885, 2007.
- Boyd, D. ; Golder, S. , and Lotan, G. . Tweet, tweet, retweet: Conversational aspects of retweeting on twitter. In *Proceedings of the 2010 43rd Hawaii International Conference on System Sciences, HICSS '10*, pages 1–10, Washington, DC, USA, 2010. IEEE Computer Society.
- Castillo, C. ; Mendoza, M. , and Poblete, B. . Information credibility on twitter. In *Proceedings of the 20th International Conference on World Wide Web, WWW '11*, pages 675–684, New York, NY, USA, 2011. ACM.
- Cataldi, M. ; Di Caro, L. , and Schifanella, C. . Emerging topic detection on twitter based on temporal and social terms evaluation. In *Proceedings of the Tenth International Workshop on Multimedia Data Mining, MDMKDD '10*, pages 4:1–4:10, New York, NY, USA, 2010. ACM.
- Cheng, Z. ; Caverlee, J. , and Lee, K. . You are where you tweet: a content-based approach to geo-locating twitter users. In *Proceedings of the 19th ACM international conference on Information and knowledge management, CIKM '10*, pages 759–768, New York, NY, USA, 2010. ACM.
- Cheong, M. and Lee, V. . Integrating web-based intelligence retrieval and decision-making from the twitter trends knowledge base. In *Proceeding of the 2nd ACM workshop on Social web search and mining, SWSM '09*, pages 1–8, New York, NY, USA, 2009. ACM.
- Cohen, J. . A coefficient of agreement for nominal scales. *Educational and psychological measurement*, 1960.
- Cui, A. ; Zhang, M. ; Liu, Y. ; Ma, S. , and Zhang, K. . Discover breaking events with popular hashtags in twitter. In *Proceedings of the 21st ACM international conference on Information and knowledge management*, pages 1794–1798. ACM, 2012.
- Fleiss, J. L. . Measuring nominal scale agreement among many raters. *Psychological bulletin*, 76(5):378, 1971.
- Hurlock, J. and Wilson, M. L. . Searching twitter: Separating the tweet from the chaff. In *Proceedings of ICWSM 2011, the 5th International AAAI Conference on Weblogs and Social Media*. AAAI, 2011.
- Jansen, B. ; Zhang, M. ; Sobel, K. , and Chowdury, A. . Twitter power: Tweets as electronic word of mouth. *Journal of the American Society for Information Science and Technology*, 60(11):2169–2188, 2009.
- Java, A. ; Song, X. ; Finin, T. , and Tseng, B. . Why we twitter: understanding microblogging usage and communities. In *Proceedings of the 9th WebKDD and 1st SNA-KDD 2007 workshop on Web mining and social network analysis, WebKDD/SNA-KDD '07*, pages 56–65, New York, NY, USA, 2007. ACM.
- Joachims, T. . Text categorization with support vector machines: learning with many relevant features. In *Proceedings of ECML-98, 10th European Conference on Machine Learning*, pages 137–142, Chemnitz, DE, 1998. Springer Verlag, Heidelberg, DE.
- Kairam, S. R. ; Morris, M. R. ; Teevan, J. ; Liebling, D. , and Dumais, S. . Towards supporting search over trending events with social media. In *Proceedings of ICWSM 2013, the 7th International AAAI Conference on Weblogs and Social Media*, 2013.
- Krishnamurthy, B. ; Gill, P. , and Arlitt, M. . A few chirps about twitter. In *Proceedings of the first workshop on Online social networks*, pages 19–24. ACM, 2008.
- Kwak, H. ; Lee, C. ; Park, H. , and Moon, S. . What is twitter, a social network or a news media? In *Proceedings of the 19th international conference on World wide web, WWW '10*, pages 591–600, New York, NY, USA, 2010. ACM.

- Landis, J. R. and Koch, G. G. . The measurement of observer agreement for categorical data. *Biometrics*, 33(1):pp. 159–174, 1977.
- Naaman, M. ; Becker, H. , and Gravano, L. . Hip and trendy: Characterizing emerging trends on twitter. *Journal of the American Society for Information Science and Technology*, 62(5):902–918, may 2011.
- Pak, A. and Paroubek, P. . Twitter as a corpus for sentiment analysis and opinion mining. In *LREC*, 2010.
- Recuero, R. ; Amaral, A. , and Monteiro, C. . Fandoms, trending topics and social capital in twitter. *Selected Papers of Internet Research*, 0(0), 2012.
- Rifkin, R. and Klautau, A. . In defense of one-vs-all classification. *The Journal of Machine Learning Research*, 5: 101–141, December 2004.
- Sakaki, T. ; Okazaki, M. , and Matsuo, Y. . Earthquake shakes twitter users: real-time event detection by social sensors. In *Proceedings of the 19th international conference on World wide web, WWW '10*, pages 851–860, New York, NY, USA, 2010. ACM.
- Sriram, B. ; Fuhry, D. ; Demir, E. ; Ferhatosmanoglu, H. , and Demirbas, M. . Short text classification in twitter to improve information filtering. In *Proceeding of the 33rd International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR '10*, pages 841–842, New York, NY, USA, 2010. ACM.
- Sun, B.-Y. ; Huang, D.-S. ; Guo, L. , and Zhao, Z.-Q. . Support vector machine committee for classification. In *Advances in Neural Networks - ISNN 2004*, pages 648–653, 2004.
- Williams, R. . The business of memes: memetic possibilities for marketing and management. *Management Decision*, 38(4):272–279, 2000.
- Wu, S. ; Hofman, J. M. ; Mason, W. A. , and Watts, D. J. . Who says what to whom on twitter. In *Proceedings of the 20th International Conference on World Wide Web, WWW '11*, pages 705–714, New York, NY, USA, 2011. ACM.
- Yang, J. and Leskovec, J. . Modeling information diffusion in implicit networks. *Data Mining, IEEE International Conference on*, 0:599–608, 2010.
- Zhao, W. X. ; Shu, B. ; Jiang, J. ; Song, Y. ; Yan, H. , and Li, X. . Identifying event-related bursts via social media activities. In *Proceedings of the 2012 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning*, pages 1466–1477. Association for Computational Linguistics, 2012.
- Zubiaga, A. ; Martínez, R. , and Fresno, V. . Getting the most out of social annotations for web page classification. In *Proceedings of the 9th ACM symposium on Document engineering, DocEng '09*, pages 74–83, New York, NY, USA, 2009. ACM.
- Zubiaga, A. ; Spina, D. ; Amigó, E. , and Gonzalo, J. . Towards real-time summarization of scheduled events from twitter streams. In *Proceedings of the 23rd ACM conference on Hypertext and social media, HT '12*, pages 319–320, New York, NY, USA, 2012. ACM.
- Zubiaga, A. ; Ji, H. , and Knight, K. . Curating and contextualizing twitter stories to assist with social newsgathering. In *Proceedings of the 2013 international conference on Intelligent user interfaces, IUI '13*, pages 213–224, New York, NY, USA, 2013. ACM.